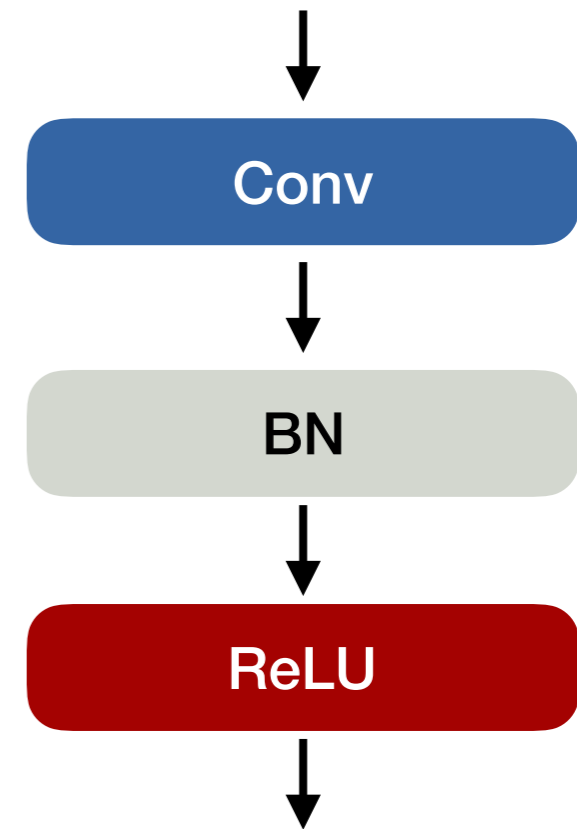


# Batch normalization

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# Batch normalization

- Make activations zero mean and unit variance



S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In ICML, 2015

# Batch normalization

$$\mathbf{Z} \in \mathbb{R}^{B \times W \times H \times C}$$



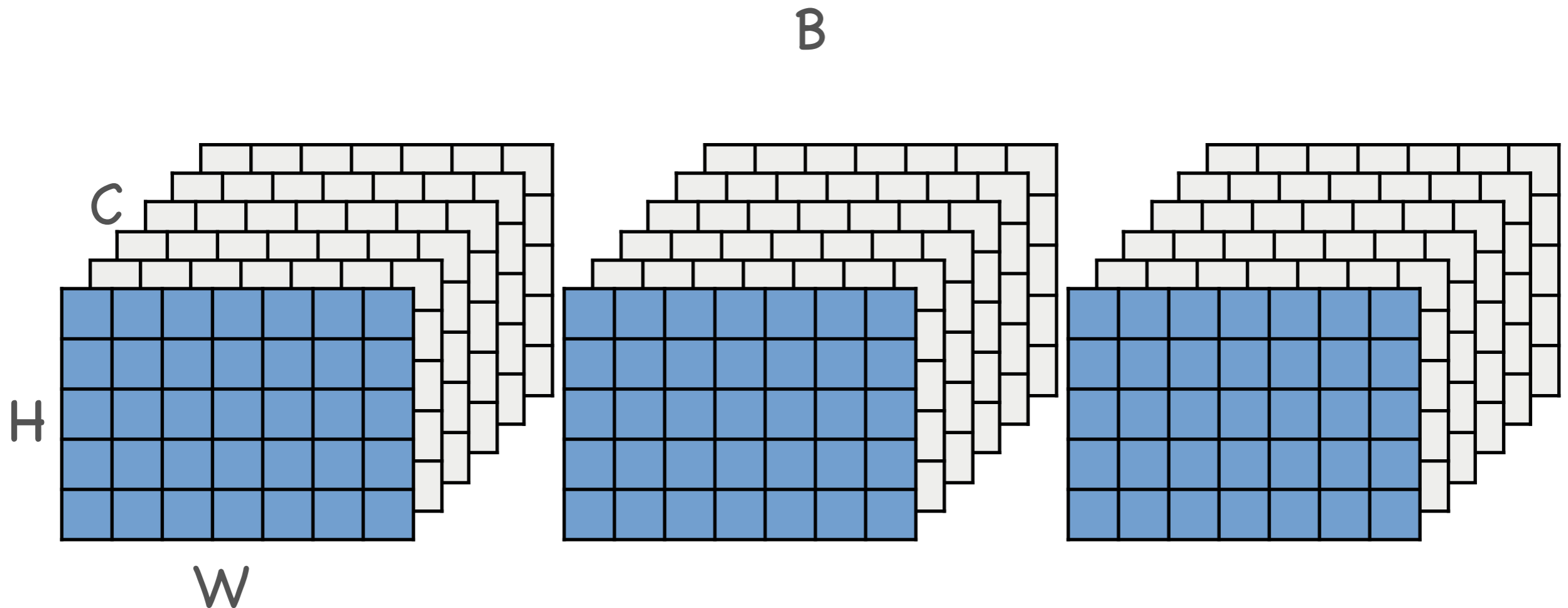
$$\frac{\mathbf{Z}_{k,x,y,c} - \mu_c}{\sigma_c}$$

- Normalize by channel-wise mean  $\mu_c$  and standard deviation  $\sigma_c$

$$\mu_c = \frac{1}{BWH} \sum_{k,x,y} \mathbf{Z}_{k,x,y,c}$$

$$\sigma_c^2 = \frac{1}{BWH} \sum_{k,x,y} (\mathbf{Z}_{k,x,y,c} - \mu_c)^2$$

# What does batch normalization do?



# What does batch normalization do?

- The good:
  - Regularizes the network
  - Handles badly scaled weights
- The bad:
  - Mixes gradient information between samples

$$\mathbf{Z} \in \mathbb{R}^{B \times W \times H \times C}$$



$$\frac{\mathbf{Z}_{k,x,y,c} - \mu_c}{\sigma_c}$$

$$\mu_c = \frac{1}{BWH} \sum_{k,x,y} \mathbf{Z}_{k,x,y,c}$$

$$\sigma_c^2 = \frac{1}{BWH} \sum_{k,x,y} (\mathbf{Z}_{k,x,y,c} - \mu_c)^2$$

# Batch norm and batch size

- Large batch sizes work better
- More stable mean and standard deviation estimates

$$\mathbf{Z} \in \mathbb{R}^{B \times W \times H \times C}$$



$$\frac{\mathbf{Z}_{k,x,y,c} - \mu_c}{\sigma_c}$$

$$\mu_c = \frac{1}{BWH} \sum_{k,x,y} \mathbf{Z}_{k,x,y,c}$$

$$\sigma_c^2 = \frac{1}{BWH} \sum_{k,x,y} (\mathbf{Z}_{k,x,y,c} - \mu_c)^2$$

# Batch norm at test time

$$\mathbf{Z} \in \mathbb{R}^{1 \times W \times H \times C}$$



$$\frac{\mathbf{Z}_{k,x,y,c} - \mu_c}{\sigma_c}$$

- Compute mean and standard deviation on training set using running average